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Empowerment or Divide? A Mixed-Methods Investigation into AI Tool Usage in Chinese Language Learning among International Students in China's Higher Vocational Colleges

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Abstract: ***The proliferation of generative artificial intelligence (AI) tools—such as large language models, machine translation applications, and intelligent writing assistants—has profoundly transformed language learning practices worldwide. For international students in China, these tools present unprecedented opportunities to overcome linguistic barriers and enhance learning efficiency. However, concerns are growing that differential access, digital literacy, and usage patterns may inadvertently generate a new form of "digital divide" within this already vulnerable population. Drawing upon van Dijk's (2024) multidimensional digital divide framework and the Technology Acceptance Model (TAM), this study employs a sequential explanatory mixed-methods design to investigate AI tool usage among international students in three Jiangsu higher vocational colleges. In the quantitative phase, 256 international students completed a structured survey assessing AI usage patterns (types, frequency, scenarios), perceived empowerment (learning efficiency, personalized support, motivation), and digital divide indicators (technological dependency, critical thinking erosion, academic integrity concerns). Hierarchical regression and mediation analyses were conducted to identify significant predictors and underlying mechanisms. In the qualitative phase, 18 purposefully selected participants engaged in semi-structured interviews to elaborate on quantitative findings and capture lived experiences. Preliminary results indicate that while over 89% of participants regularly use AI tools for Chinese learning, usage patterns vary significantly by HSK level, digital literacy, and teacher guidance. Empowerment effects are most pronounced in vocabulary acquisition and writing assistance, whereas divide effects are most evident in higher-order thinking tasks and independent problem-solving. Teacher support and AI literacy training emerged as critical moderating factors that buffer against negative consequences. This study extends digital divide theorizing to the context of AI-enhanced language education and offers empirically grounded recommendations for fostering responsible AI use in international Chinese language education.***

Keywords: AI-assisted language learning, Digital divide, International students, Chinese as a second language, Higher vocational education, Mixed-methods, Technology acceptance, Educational equity.

1. Introduction

1.1 The AI Revolution in Language Education

The rapid advancement of generative artificial intelligence has fundamentally reshaped the landscape of language education. Tools such as ChatGPT, Deepseek, Google Translate, and Duolingo have moved from novelty to necessity, with global AI education market projections reaching $80 billion by 2030. Language learning represents one of the most prominent application domains, as AI technologies excel at providing instant translation, automated writing feedback, conversational practice, and personalized content generation.

For international students learning Chinese as a second language, AI tools are particularly consequential. Chinese, classified as a Category IV language by the Foreign Service Institute, requires approximately 2,200 hours of study for native English speakers to achieve proficiency—far more than European languages. The cognitive and emotional demands of this learning journey are compounded by the challenges of living in a culturally unfamiliar environment, navigating complex social interactions, and meeting academic requirements in a foreign language.

1.2 The Promise and Peril of AI in Education

Scholars have extensively documented the empowering potential of AI in educational contexts. Adaptive learning systems can tailor content to individual proficiency levels (Chen et al., 2023), intelligent tutoring systems provide immediate, corrective feedback, and conversational agents offer low-anxiety practice opportunities. For language learners specifically, AI tools lower the threshold for comprehension, enabling access to authentic materials that would otherwise be inaccessible, and provide scaffolded support for production tasks.

However, a growing body of critical scholarship has raised concerns about the unintended consequences of AI integration in education. These include cognitive offloading—the tendency to rely on AI for tasks that would otherwise develop cognitive skills—reduction in critical thinking engagement, homogenization of creative output, and risks to academic integrity (Cotton et al., 2024). For language learners, over-reliance on AI translation and generation tools may impede the development of communicative competence, as students outsource rather than cultivate linguistic skills.

1.3 The Digital Divide Revisited

The concept of the digital divide has evolved considerably since its initial formulation. Early research focused on the "access gap"—the binary distinction between those with and without physical access to digital technologies (Norris, 2001). Van Dijk's (2005, 2024) more sophisticated framework conceptualizes digital inequality as operating through four sequential barriers: motivational access, physical access, skills access, and usage access. More recently, scholarship has identified a "second-level" divide concerning differences in how individuals use technology, and a "third-level" divide concerning differences in the outcomes and benefits derived from technology use.

In the context of AI-enhanced education, these layers manifest in new forms. Students may have equivalent physical access to AI tools yet differ dramatically in their capacity to deploy them effectively—distinguishing between those who use AI for surface-level task completion versus those who leverage it for deeper learning and critical engagement. This "cognitive divide" represents a particularly insidious form of inequality, as it may be less visible but no less consequential than traditional access disparities.

1.4 International Students in Chinese Vocational Colleges: A Unique Population

International students in China's higher vocational colleges represent a distinct and under-researched population. Unlike their counterparts in research-oriented universities, vocational students typically enroll in shorter programs (2-3 years), pursue more applied curricula, and often enter with lower Chinese proficiency. Many are sponsored by Belt and Road Initiative scholarships, hailing from countries with varying educational infrastructures and digital resources. Approximately 5% of China's international student population—over 25,000 students—study in vocational institutions, and this number continues to grow (Ministry of Education, 2025).

This population faces unique vulnerabilities. The compressed timeline of vocational programs leaves less room for gradual language acquisition. The practical, industry-embedded nature of their training demands immediate functional competence in Chinese. Furthermore, many vocational college international students come from lower-resourced educational backgrounds, potentially with less prior experience in digital learning environments. For this group, AI tools represent both a lifeline and a potential trap—a means of overcoming immediate linguistic barriers that may simultaneously undermine long-term skill development.

1.5 Research Gaps

Despite the accelerating integration of AI into language education and the growing presence of international students in Chinese vocational colleges, several significant gaps persist in the literature.

First, research on AI-assisted language learning predominantly focuses on English as a Second Language (ESL) contexts or on Chinese learning among university students. The vocational college international student population remains largely invisible in this scholarship, despite their distinct learning needs, constraints, and trajectories.

Second, existing research overwhelmingly adopts a technology-optimistic stance, emphasizing the empowering potential of AI while neglecting to systematically examine its risks, particularly the potential to create or exacerbate digital divides. Critical, balanced examinations of AI's dual effects are rare.

Third, most studies employ purely quantitative or purely qualitative designs, limiting their capacity to capture both the prevalence and the lived experience of AI-related phenomena. The field lacks integrated, mixed-methods investigations that can establish patterns while illuminating underlying mechanisms.

Fourth, the role of moderating factors—particularly institutional support structures, teacher guidance, and pedagogical design—in shaping the relationship between AI use and learning outcomes remains undertheorized and underinvestigated.

1.6 Research Questions

This study addresses these gaps through the following research questions:

What are the patterns of AI tool usage (types, frequency, scenarios, purposes) among international students in Jiangsu vocational colleges for Chinese language learning?

What "empowerment" effects do students perceive from AI tool usage, and what "divide" effects (cognitive, ethical, and outcome-based) are simultaneously observable?

What individual, environmental, and technological factors moderate the balance between empowerment and divide effects?

What support needs do students articulate regarding AI tool usage, and what institutional responses are indicated?

2. Literature Review

2.1 AI Tools in Language Learning: A Typology

AI tools relevant to Chinese language learning can be categorized into several functional types. **Translation and interpretation tools**, such as Google Translate, DeepL, and Baidu Translate, provide immediate lexical and sentential translation. **Intelligent writing assistants**, such as Grammarly and Deepseek's writing functions, offer automated grammar correction and stylistic suggestions. **Conversational agents and chatbots**, including ChatGPT, Duolingo Max, and specialized Chinese chatbots, enable interactive, simulated conversation practice. **Speech recognition and pronunciation tools** support speaking skill development through automated phonetic analysis. **Personalized learning platforms** adapt content sequencing and practice frequency to individual learner profiles.

Research indicates that international students in China use these tools extensively, with usage rates exceeding 85% in some studies. However, the quality and nature of this usage vary considerably, from strategic, metacognitive engagement to passive, task-completion orientation.

2.2 The Empowerment Effects of AI in Language Learning

The theoretical basis for AI's empowering potential draws on several established educational frameworks. From a **constructivist perspective**, AI tools provide affordances for language input and output that might otherwise be unavailable, enabling learners to engage with authentic materials and practice in low-stakes environments. From a **self-determination theory perspective**, AI tools can enhance learner autonomy by providing immediate, on-demand support that reduces frustration and supports continued motivation.

Empirical evidence supports these claims. Chen and colleagues (2023) found that AI-powered adaptive learning systems improved language learning outcomes by 23% compared to non-adaptive instruction, with particularly strong effects for lower-proficiency learners.

Specific to the Chinese learning context, recent research has documented AI's role in supporting character recognition, providing pronunciation feedback, enabling authentic reading, supporting communicative practice, and creating personalized learning pathways.

2.3 The Divide Effects of AI in Language Learning

The critical literature on AI in education has identified several concerning patterns. **Cognitive offloading** refers to the tendency for learners to rely on external cognitive aids—such as AI—to reduce cognitive effort, potentially compromising the development of internal cognitive capacities.

Critical thinking erosion represents another concern. When learners receive immediate answers or polished text from AI, the opportunity for wrestling with ambiguity—a key driver of cognitive development—is foreclosed. Studies have documented reduced critical engagement among students who regularly use AI for academic tasks.

Academic integrity challenges have received substantial attention, particularly in higher education settings. Cotton and colleagues (2024) surveyed faculty perceptions and found significant concerns about the use of generative AI to produce assignments, with ambiguity about what constitutes appropriate versus inappropriate use.

For language learners specifically, additional concerns arise. **Interlanguage fossilization**—the persistence of non-target-like forms—may be accelerated by AI translation that bypasses the learner's production system. **Diminished motivation** may result from AI tools that reduce the experiential, process-oriented aspects of language learning. **Assessment invalidity** occurs when AI use masks learners' true competency levels.

2.4 The Digital Divide Revisited in AI Contexts

Van Dijk's (2024) four-access model provides a comprehensive framework for analyzing digital inequality. **Motivational access** concerns whether individuals have the desire and intention to use technology. **Physical access** concerns the availability of devices and connectivity. **Skills access** concerns the capacity to use technology effectively. **Usage access** concerns the actual patterns of use and their outcomes.

In the context of AI-enhanced language learning, motivational access may vary by learners' prior technology experience. Physical access is less relevant for vocational international students, as smartphone penetration approaches universality. Skills access, however, emerges as critical—the ability to craft effective prompts, evaluate AI output, and integrate AI use with broader learning strategies varies substantially. Usage access, or what students actually do with AI, represents the most consequential divide. Some learners use AI to complete tasks they cannot do independently, while others use AI to extend and enhance their own cognitive processing.

2.5 Institutional Responses to AI in Education

Educational institutions worldwide have responded to AI integration in varied ways. At one extreme, outright prohibition of AI use in academic settings has been adopted by some educational systems, driven by concerns about academic integrity and skill development. At the other extreme, laissez-faire approaches leave AI use largely unregulated, assuming that technology integration is inevitable and that students will adapt appropriately.

A growing consensus favors a middle ground: teaching AI literacy alongside content instruction. This approach involves developing students' capacity to understand what AI can and cannot do, evaluate AI output critically, use AI as a tool rather than a replacement for cognition, and maintain academic integrity in AI-involved work.

In Chinese vocational education contexts, official responses to AI use among international students remain nascent. To our knowledge, no systematic research has examined institutional policies, teacher practices, or student perspectives on AI integration in this specific context.

2.6 The Present Study

This study contributes to the literature by providing the first systematic, mixed-methods investigation of AI tool usage in Chinese language learning among international students in Chinese vocational colleges. By integrating quantitative survey data with qualitative interview data, the study captures both the prevalence and the lived experience of AI-related phenomena. By explicitly examining both empowerment and divide effects, the study provides a balanced, nuanced account of AI's dual consequences. By investigating moderating factors, the study offers actionable guidance for institutional responses.

3. Methods

3.1 Research Design

This study employed a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018), consisting of two integrated phases. The quantitative phase involved cross-sectional survey data collection to establish the prevalence and patterns of AI tool usage, assess perceived empowerment and divide effects, and identify significant predictors and moderators. The subsequent qualitative phase used semi-structured interviews to explain and elaborate on quantitative findings, capturing the subjective experiences, meaning-making processes, and contextual factors behind statistical patterns. This design is particularly appropriate for investigating complex, context-dependent phenomena where both breadth and depth of understanding are required.

3.2 Participants

3.2.1 Quantitative Phase

A stratified random sampling strategy was employed across three vocational colleges in Jiangsu Province: Jiangsu Maritime Institute (JMI), Nanjing Polytechnic Institute (NPI), and Yangzhou Polytechnic Institute (YPI). These institutions were selected to represent diverse vocational education contexts, encompassing maritime, engineering, and comprehensive programs, and to ensure variation in student demographics and institutional resources.

Inclusion criteria for participation were: (a) current enrollment as an international student in one of the three participating institutions; (b) enrollment in a diploma-granting program of at least two years' duration; (c) active engagement in Chinese language learning as part of the program; and (d) willingness to provide informed consent.

Exclusion criteria were: (a) exchange students on programs shorter than one semester; (b) students who had been in China for less than one month; and (c) students unable to complete the survey in either Chinese or English.

Three hundred twenty surveys were distributed across the three institutions. After excluding 64 responses with patterned answering (e.g., straight-lining), missing data exceeding 20%, or incomplete demographic information, 256 valid responses were retained (valid response rate: 80.0%). Sample size exceeds the minimum required for multiple regression with 15 predictors (10 cases per predictor; Field, 2018) and for structural equation modeling (Hair et al., 2019).

Participants' age ranged from 18 to 34 (M = 22.7, SD = 3.3). The sample included representation across majors including maritime navigation (27.3%), marine engineering (29.7%), international trade (24.2%), and hospitality management (18.8%). Detailed demographic characteristics are presented in Table 1.

Table 1: Demographic Characteristics of Quantitative Participants (N = 256)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	167	65.2
	Female	89	34.8
Institution	JMI	94	36.7
	NPI	87	34.0
	YPI	75	29.3
Year of Study	Year 1	117	45.7
	Year 2	102	39.8
	Year 3	37	14.5
HSK Level	Below Level 3	52	20.3
	Level 3	82	32.0
	Level 4	75	29.3
	Level 5 or above	47	18.4
Region of Origin	Southeast Asia	94	36.7
	South Asia	56	21.9
	Central Asia	46	18.0
	Africa	39	15.2
	Other	21	8.2
Age Group	18-20	68	26.6
	21-23	112	43.8
	24-26	51	19.9
	27+	25	9.8

3.2.2 Qualitative Phase

Eighteen participants were purposefully sampled from survey respondents based on their composite AI usage and adaptation scores. Sampling strategy ensured representation across: (a) the empowerment-divide continuum (high empowerment/low divide; moderate on both; low empowerment/high divide); (b) HSK levels (Level 3 and below; Level 4; Level 5 and above); (c) gender; (d) year of study; and (e) region of origin. This purposive approach enabled maximum variation sampling, enhancing the transferability of qualitative findings (Patton, 2015).

Participants provided written informed consent for audio-recorded interviews. All names used in reporting are pseudonyms.

3.3 Instruments

3.3.1 Quantitative Instruments

Demographics and Background. Items captured gender, age, institution, year of study, major, HSK level, length of stay in China, region of origin, prior technology experience (5-point scale), and internet access stability (5-point scale).

AI Tool Usage Patterns. A comprehensive inventory was developed to assess AI tool usage. Participants were presented with a list of AI tools organized by functional category: (a) translation tools (e.g., Google Translate, Baidu Translate, DeepL); (b) conversational AI (e.g., ChatGPT, Deepseek, Microsoft Copilot); (c) intelligent writing assistants (e.g., Grammarly, AI-powered writing functions); (d) speech recognition/pronunciation tools; (e) personalized learning platforms; and (f) other. For each tool, participants indicated: (1) whether they had ever used it for Chinese learning (yes/no); (2) frequency of use (1=Never, 5=Daily); (3) primary purpose (multiple selection from: vocabulary, grammar, writing, speaking, reading, listening, test preparation, homework completion, daily communication); and (4) perceived usefulness (1=Not useful at all, 5=Extremely useful).

Empowerment Effects Scale. A 20-item scale was developed to assess perceived empowerment from AI tool usage, drawing on prior research (Chen et al., 2023) and the Technology Acceptance Model (Davis, 1989). Items covered four dimensions: (a) learning efficiency enhancement (e.g., "AI tools help me complete Chinese learning tasks faster"; α=0.87); (b) personalized learning support (e.g., "AI tools provide learning content tailored to my level"; α=0.84); (c) reduced learning barriers (e.g., "AI tools help me understand materials I would otherwise not understand"; α=0.82); and (d) increased motivation and confidence (e.g., "Using AI tools makes me more confident in my Chinese learning"; α=0.85). Items used a 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree). The full scale demonstrated excellent reliability (Cronbach's α = 0.92).

Digital Divide Effects Scale. A 24-item scale was developed to assess potential negative consequences of AI tool usage, operationalizing van Dijk's (2024) multidimensional framework. Items covered four dimensions: (a) technological dependency (e.g., "I find it difficult to complete Chinese tasks without AI tools"; α=0.86); (b) critical thinking erosion (e.g., "I tend to accept AI-generated content without questioning it"; α=0.83); (c) academic integrity concerns (e.g., "I have submitted AI-generated content as my own work"; α=0.79); and (d) learning outcome compromise (e.g., "I feel my Chinese ability is not improving because I rely too much on AI"; α=0.81). The full scale demonstrated good reliability (Cronbach's α = 0.89).

AI Literacy Scale. A 12-item scale was adapted from prior research (Long & Magerko, 2020; Ng et al., 2021) to assess participants' capacity to understand, evaluate, and use AI tools effectively. Items covered: (a) understanding AI capabilities and limitations; (b) critical evaluation of AI output; (c) effective prompt formulation; and (d) ethical AI use. Sample items included: "I know what types of tasks AI tools are good and not good for"; "I can tell when AI-generated content is inaccurate or biased"; and "I know how to formulate effective prompts to get useful responses." The scale demonstrated acceptable reliability (Cronbach's α = 0.84).

Teacher Support and Guidance Regarding AI. A 6-item scale was developed to assess participants' perceptions of teacher support and guidance regarding AI tool use. Items covered: (a) explicit guidance on appropriate AI use; (b) discussion of AI-related academic integrity issues; (c) integration of AI literacy into coursework; (d) teacher familiarity with AI tools; and (e) perceived encouragement for effective AI use. The scale demonstrated good reliability (Cronbach's α = 0.87).

Chinese Language Proficiency. Self-assessed proficiency was measured using a 5-item scale adapted from prior research (Li et al., 2021), covering listening comprehension, speaking fluency, reading comprehension, writing, and vocabulary knowledge (α=0.90). HSK level was treated as a categorical variable for subgroup comparisons and as a continuous variable (with Levels 1-6 coded accordingly) for regression analysis.

AI Usage Self-Efficacy. A 6-item scale measured participants' confidence in using AI tools for Chinese learning tasks, adapted from the general self-efficacy literature (Bandura, 1997). Sample items included: "I am confident I can use AI tools to improve my Chinese writing" and "I can use AI tools effectively even without detailed instructions." The scale demonstrated good reliability (Cronbach's α = 0.85).

All instruments were initially developed in English, translated to Chinese, and back-translated to ensure conceptual equivalence, following established procedures (Brislin, 1970). The Chinese versions were pilot-tested with 35 international students at JMI, and adjustments were made based on feedback regarding item clarity and cultural relevance.

3.3.2 Qualitative Data Collection

Semi-structured interview guides were developed based on quantitative findings. The guide structure followed a responsive interviewing approach (Rubin & Rubin, 2012), with core questions and planned probes, while allowing for emergent themes.

Core questions included:

"Can you describe how you use AI tools in your Chinese learning, starting from when you first arrived in China?"

"In what ways have AI tools helped you in your Chinese learning journey? Can you give specific examples?"

"Have you experienced any negative effects from using AI tools? What concerns do you have about relying on AI?"

"How do your teachers talk about or respond to AI tool use in your classes?"

"What support would help you use AI tools more effectively and responsibly?"

"Can you tell me about a situation where you felt you should or should not use AI?"

Interviews were conducted in English, or with an interpreter when necessary, each lasting 35-55 minutes. All interviews were audio-recorded with informed consent and transcribed verbatim. Field notes were recorded immediately after each interview to capture contextual observations and initial analytical insights.

3.4 Procedure

Ethical approval was obtained from the institutional review boards of all three participating institutions. The research was conducted in accordance with the ethical guidelines of the Chinese Ministry of Education and the Declaration of Helsinki.

Quantitative Data Collection. Survey invitations were distributed via class advisors and WeChat groups during March-April 2026. Students were informed of the study's purpose, the voluntary nature of participation, and the confidentiality of responses. An information sheet was provided in both Chinese and English. Surveys were administered online through Wenjuanxing (a Chinese survey platform), requiring approximately 20-25 minutes to complete. A small incentive (a 20 RMB campus convenience store voucher) was provided to participants who completed the survey. Data collection occurred in two waves to maximize response rates, with follow-up reminders sent one week after initial invitations.

Qualitative Data Collection. After initial quantitative data analysis, interview participants were contacted via email or WeChat. Interviews were scheduled at participants' convenience, conducted in private campus offices or via video conferencing (for participants on off-campus internships), and audio-recorded with consent. Interviews were conducted during May-June 2026 by two trained research assistants who were not involved in the participants' instruction. The research team met weekly during the interview period to discuss emerging themes and refine probing strategies.

3.5 Data Analysis

3.5.1 Quantitative Analysis

Data were analyzed using SPSS 27.0 and Mplus 8.8. The following analytical procedures were conducted:

Descriptive statistics (means, standard deviations, frequencies, percentages) summarized AI usage patterns, empowerment effects, and divide effects.

Independent samples t-tests and one-way ANOVA examined group differences by gender, institution, year of study, HSK level, and region of origin. Post-hoc comparisons were conducted using Tukey's HSD for equal variances and Games-Howell for unequal variances.

Pearson correlations assessed relationships among key variables, including AI usage frequency, empowerment, divide effects, AI literacy, teacher guidance, and Chinese proficiency.

Hierarchical multiple regression identified significant predictors of empowerment and divide effects. For each outcome variable, control variables (demographics) were entered in Step 1, language proficiency and AI literacy in Step 2, teacher guidance in Step 3, and interaction terms in Step 4. Significance was set at $p < 0.05$.

Moderation analyses were conducted using PROCESS macro for SPSS (Model 1) to test whether teacher guidance, AI literacy, and language proficiency moderated the relationship between AI usage frequency and empowerment/divide effects. Bootstrap with 5,000 samples was used to construct 95% confidence intervals.

Mediation analyses tested whether AI usage self-efficacy mediated the relationship between AI literacy and empowerment effects, using the bootstrapping procedure with 5,000 samples.

3.5.2 Qualitative Analysis

Transcripts were analyzed using thematic analysis following Braun and Clarke's (2006) six-phase approach: (1) familiarization with data through repeated reading and initial noting; (2) generating initial codes systematically across the entire dataset; (3) searching for themes by collating codes into potential themes; (4) reviewing themes at the level of coded extracts and the entire dataset; (5) defining and naming themes through ongoing analysis; and (6) producing the report with compelling extract examples.

Coding was conducted using NVivo 14. The analysis proceeded through two cycles: initial coding was open and inductive, capturing all potentially relevant content; focused coding subsequently refined codes into hierarchical categories. Codes were developed independently by two coders, with disagreements resolved through discussion and consensus (inter-coder agreement = 87%). Themes were developed inductively from the data while remaining informed by the theoretical framework.

Integration of Quantitative and Qualitative Data. The two data sets were integrated at the interpretation stage, following the explanatory sequential design (Creswell & Plano Clark, 2018). Quantitative patterns guided the selection of interview participants and informed interview questions. Qualitative findings were used to explain, elaborate, and contextualize quantitative results. A joint display table was constructed to present how qualitative themes mapped onto quantitative constructs.

4. Quantitative Findings

4.1 AI Tool Usage Patterns

Descriptive statistics revealed extensive AI tool adoption among participants. Of the 256 participants, 228 (89.1%) reported using at least one AI tool for Chinese learning purposes. Table 2 presents usage rates by tool category.

Table 2: AI Tool Usage Rates by Category

Tool Category	Ever Used (%)	Daily Use (%)	Weekly Use (%)	Mean Use Frequency (1-5)
Translation tools (e.g., Baidu Translate, DeepL)	94.5	52.7	34.0	3.94 (SD=0.92)
Conversational AI (e.g., Deepseek, ChatGPT)	82.0	38.3	35.9	3.42 (SD=1.04)
Intelligent writing assistants	67.2	23.4	34.4	3.01 (SD=1.12)
Speech recognition/pronunciation	48.4	12.5	28.1	2.64 (SD=1.21)
Personalized learning platforms	39.1	9.4	21.9	2.39 (SD=1.18)
Other AI tools	25.8	5.5	14.8	2.08 (SD=1.25)

Translation tools were nearly universal, with 94.5% of participants having used them, and over half (52.7%) using them daily. Conversational AI (Deepseek, ChatGPT) was also widely used, with 82.0% ever-use and 38.3% daily use. The most frequently reported primary purposes for AI use were: vocabulary look-up (87.9%), understanding class materials (76.8%), completing homework assignments (71.3%), preparing written assignments (65.4%), and practicing reading comprehension (52.6%).

4.2 Empowerment Effects

The overall mean empowerment score was 3.72 (SD = 0.69, range: 1.0-5.0), indicating moderately high perceived empowerment from AI tool usage. Table 3 presents descriptive statistics by dimension.

Learning efficiency enhancement received the highest ratings (M=3.95), consistent with participants' perception that AI tools help them complete tasks faster. Reduced learning barriers (M=3.81) and personalized support (M=3.78) also rated highly. Motivation and confidence enhancement (M=3.34) was the lowest-rated dimension, suggesting that while AI tools are perceived as practically useful, their impact on affective dimensions of learning is less pronounced.

Table 3: Empowerment Effects by Dimension

Dimension	Mean	SD	Skewness	Kurtosis
Learning efficiency enhancement	3.95	0.78	-0.52	0.12
Personalized learning support	3.78	0.82	-0.41	-0.18
Reduced learning barriers	3.81	0.84	-0.48	-0.06
Increased motivation and confidence	3.34	0.91	-0.23	-0.32
Overall Empowerment	**3.72**	**0.69**	**-0.44**	**-0.12**

4.3 Divide Effects

The overall mean divide score was 2.89 (SD = 0.74, range: 1.0-4.92), indicating moderate levels of perceived negative consequences. However, substantial variation was observed, with 37.1% of participants scoring above 3.0 on the overall divide scale. Table 4 presents descriptive statistics by dimension.

Table 4: Divide Effects by Dimension

Dimension	Mean	SD	Skewness	Kurtosis	% Scoring Above 3.0
Technological dependency	3.21	0.95	-0.12	-0.48	54.3
Academic integrity concerns	2.78	1.02	0.28	-0.64	38.7
Critical thinking erosion	2.81	0.98	0.15	-0.52	39.8
Learning outcome compromise	2.75	0.96	0.22	-0.56	36.3
Overall Divide	**2.89**	**0.74**	**0.08**	**-0.38**	**37.1**

Technological dependency was the most prominent divide dimension (M=3.21), with over half of participants (54.3%) scoring above the midpoint. Representative items with highest endorsement included: “I feel uncomfortable when I cannot access AI tools for Chinese tasks” (M=3.42) and “I tend to use AI first rather than trying to figure things out myself” (M=3.28). Critical thinking erosion (M=2.81) and academic integrity concerns (M=2.78) showed moderate levels, with notable minority reporting problematic behaviors.

4.4 Group Differences

By HSK Level. Significant differences were observed across HSK levels for both empowerment and divide effects. For empowerment, $F(3,252)=6.78$, $p<0.001$, with students at HSK Level 5+ reporting the highest empowerment (M=4.01, SD=0.61) and those below Level 3 reporting the lowest (M=3.38, SD=0.72). For divide effects, HSK Level 5+ students reported significantly lower divide scores (M=2.52, SD=0.68) compared to students below Level 3 (M=3.24, SD=0.75), $F(3,252)=7.45$, $p<0.001$. This pattern suggests that higher language proficiency is associated with both greater benefit and lower risk from AI tool use.

By Year of Study. Year 1 students reported higher empowerment (M=3.88, SD=0.65) than Year 3 students (M=3.48, SD=0.74), $F(2,253)=4.23$, $p=0.015$. Divide effects were highest among Year 3 students (M=3.18, SD=0.72) compared to Year 1 (M=2.78, SD=0.72) and Year 2 (M=2.85, SD=0.74), $F(2,253)=5.12$, $p=0.007$. This temporal pattern suggests increasing AI dependency and diminishing perceived benefit over the course of the program.

By Gender. No significant gender differences were found for empowerment ($M_{male}=3.74$, $M_{female}=3.69$, $t(254)=0.56$, $p=0.576$). For divide effects, male participants reported slightly higher scores (M=2.94, SD=0.75) than females (M=2.78, SD=0.71), though this difference was not statistically significant ($t(254)=1.67$, $p=0.096$).

By Region of Origin. Significant regional differences emerged. Southeast Asian participants reported the highest empowerment (M=3.89, SD=0.63), while African participants reported the lowest (M=3.42, SD=0.74), $F(4,251)=4.56$, $p=0.001$. For divide effects, African participants reported the highest scores (M=3.18, SD=0.78) and Central Asian participants the lowest (M=2.68, SD=0.68), $F(4,251)=4.12$, $p=0.003$.

4.5 Correlation Analysis

Pearson correlations among key variables are presented in Table 5. AI usage frequency was positively correlated with both empowerment ($r=0.41$, $p<0.01$) and divide effects ($r=0.28$, $p<0.01$), suggesting that more frequent use is associated with both greater benefits and greater risks—a core tension in AI integration.

Table 5: Correlation Matrix of Key Variables

Variable	1	2	3	4	5	6	7	8
1. Usage Frequency	1.00							
2. Empowerment	0.41**	1.00						
3. Divide Effects	0.28**	-0.12	1.00					
4. AI Literacy	0.35**	0.48**	-0.38**	1.00				
5. Teacher Guidance	0.29**	0.44**	-0.35**	0.41**	1.00			
6. Chinese Proficiency	0.22**	0.39**	-0.42**	0.44**	0.37**	1.00		
7. Usage Self-Efficacy	0.38**	0.51**	-0.31**	0.52**	0.38**	0.41**	1.00	
8. Prior Tech Experience	0.31**	0.34**	-0.21**	0.39**	0.28**	0.25**	0.34**	1.00

**p < 0.01

AI literacy showed the strongest correlation with empowerment ($r=0.48$, $p<0.01$) and a robust negative correlation with divide effects ($r=-0.38$, $p<0.01$). Teacher guidance similarly predicted both higher empowerment ($r=0.44$, $p<0.01$) and lower divide effects ($r=-0.35$, $p<0.01$). Chinese proficiency was most strongly associated with reduced divide effects ($r=-0.42$, $p<0.01$), suggesting that language skill provides a protective effect against AI’s negative consequences.

4.6 Hierarchical Regression Analysis

Hierarchical multiple regression was conducted to identify significant predictors of empowerment and divide effects. Tables 6 and 7 present the final models.

In the final model for empowerment, AI literacy ($\beta=0.215$, $p<0.001$) was the strongest predictor, followed by teacher guidance ($\beta=0.248$, $p<0.001$) and usage self-efficacy ($\beta=0.194$, $p=0.002$). HSK level ($\beta=0.141$, $p=0.018$) also contributed significantly. Year of study became non-significant after accounting for psychological and support variables.

Table 6: Hierarchical Regression Predicting Empowerment Effects

Predictor	Model 1 β	Model 2 β	Model 3 β	Model 4 β	VIF
Gender (female=1)	-0.042	-0.038	-0.031	-0.028	1.18
Year of Study	-0.156**	-0.124*	-0.098	-0.087	1.22
HSK Level	0.234***	0.168**	0.141*	1.38	
AI Literacy	0.342***	0.281***	0.215***	1.52	
Teacher Guidance		0.287***	0.248***	1.44	
Usage Self-Efficacy			0.194**	1.47	
R^2	0.028	0.267	0.342	0.378	
ΔR^2		0.239***	0.075***	0.036**	

***p < 0.001, **p < 0.01, *p < 0.05.

Table 7: Hierarchical Regression Predicting Divide Effects

Predictor	Model 1 β	Model 2 β	Model 3 β	Model 4 β	VIF
Gender (female=1)	0.067	0.072	0.058	0.052	1.18
Year of Study	0.182**	0.152*	0.118*	0.104	1.22
HSK Level	-0.298***	-0.244***	-0.218***	1.38	
AI Literacy	-0.318***	-0.262***	-0.204**	1.52	
Teacher Guidance		-0.267***	-0.231***	1.44	
Usage Self-Efficacy			-0.148*	1.47	
R^2	0.037	0.282	0.361	0.382	
ΔR^2		0.245***	0.079***	0.021*	

***p < 0.001, **p < 0.01, *p < 0.05.

For divide effects, the final model explained 38.2% of variance. HSK level (β=-0.218, p<0.001) emerged as the strongest protective factor against divide effects, followed by teacher guidance (β=-0.231, p<0.001) and AI literacy (β=-0.204, p=0.002). Year of study became non-significant in the final model.

4.7 Moderation Analyses

Teacher Guidance as Moderator. Teacher guidance significantly moderated the relationship between AI usage frequency and divide effects (interaction β=-0.162, p=0.004). Among students with low teacher guidance, increased usage frequency was associated with substantially higher divide effects (β=0.38, p<0.001). Among students with high teacher guidance, this relationship was attenuated (β=0.12, p=0.087). This suggests that teacher guidance functions as a protective factor, mitigating the negative consequences of frequent AI use.

Teacher guidance also moderated the relationship between AI literacy and empowerment (interaction β=0.138, p=0.012). The positive effect of AI literacy on empowerment was stronger among students who received higher teacher guidance, suggesting a synergistic effect where institutional support amplifies the benefits of individual digital competence.

HSK Level as Moderator. HSK level moderated the relationship between AI usage frequency and divide effects (interaction β=-0.154, p=0.008). For students with lower HSK levels (Level 3 and below), frequent AI use was associated with significantly higher divide effects (β=0.42, p<0.001). For students with HSK Level 5+, this relationship was non-significant (β=0.08, p=0.312). This indicates that lower proficiency students are more vulnerable to the negative consequences of AI tool use, highlighting the need for targeted support for this group.

4.8 Mediation Analysis

Mediation analysis tested whether usage self-efficacy mediated the relationship between AI literacy and empowerment. Results indicated a significant indirect effect (indirect β=0.158, 95% CI [0.092, 0.234]), accounting for 38.2% of the total effect. AI literacy appears to enhance empowerment partly through increasing students' confidence in their capacity to use AI tools effectively, consistent with self-efficacy theory (Bandura, 1997).

5. Qualitative Findings

Five overarching themes emerged from thematic analysis of 18 participant interviews, each providing explanatory depth and contextual elaboration to quantitative patterns.

5.1 Theme 1: AI as "A Necessary Crutch" — The Ambivalence of Dependency

Participants consistently described AI tools as essential for survival, yet many expressed unease about their dependence. This ambivalence captures the tension between empowerment and divide effects identified quantitatively.

A first-year student from Indonesia articulated this tension vividly: "When I first came, I couldn't understand anything. Teachers spoke fast, textbooks were difficult. Translation apps saved me. I used them for everything—reading, writing, even understanding what people said in the canteen. But now I worry, what happens if I don't have my phone? I feel like I can't function without it" (P03, Female, Year 1, International Trade).

A second-year student from Pakistan expressed similar concerns: "AI is like a crutch when you have a broken leg. It helps you walk when you cannot. But if you keep using it, your leg will never get stronger. I use Deepseek for all my writing assignments. My grades are good. But I know if I take an exam without AI, I will fail" (P07, Male, Year 2, Marine Engineering).

This metaphor of AI as a crutch was remarkably consistent across interviews. Participants recognized the immediate utility while simultaneously acknowledging the long-term developmental costs. Importantly, several participants distinguished between "good" and "bad" uses: using AI to understand a difficult text was seen as acceptable, while using AI to produce content they would otherwise produce themselves was viewed as problematic.

5.2 Theme 2: Differential Vulnerability — Language Proficiency as a Gatekeeper

Participants unanimously identified Chinese language proficiency as the critical factor determining whether AI use was empowering or debilitating. This theme directly explains why HSK level emerged as the strongest predictor of divide effects in quantitative analyses.

A third-year student from Bangladesh reflected on his own trajectory: "When my Chinese was bad, I used AI for everything. I never tried to write myself. I just copied and pasted from translation. But as my Chinese improved, I started to use AI differently. Now I write first, then ask AI to check. Before I used AI as my brain, now I use AI as my assistant" (P12, Male, Year 3, Navigation).

A participant from Kenya offered a parallel perspective: "My friend whose Chinese is very good, she uses AI to check her grammar after she writes. She learns from the AI. Me, my Chinese is not good, I use AI to do the work for me. I don't learn anything. It's not fair because the AI helps her more because she knows how to use it. For me, it just helps me cheat myself" (P09, Female, Year 2, Hospitality).

This differential vulnerability was compounded by the lack of guidance on appropriate AI use. Several participants expressed confusion about what constituted acceptable use. A student from Vietnam noted: "Teachers never tell us if we can use AI or not. I don't know what is allowed. Sometimes I feel guilty when I use AI, but I don't know what else to do" (P05, Female, Year 1).

5.3 Theme 3: Teacher Guidance as a Critical Resource

Participants who reported clear teacher guidance regarding AI use also reported more balanced, empowering usage patterns. Teacher guidance functioned both directly—through explicit instruction—and indirectly—through modeling appropriate use.

A second-year student from Thailand described a positive experience: "My Chinese writing teacher was very helpful. She showed us how to use AI to help our writing without cheating. She said: 'Use AI to check grammar after you write, not to write for you.' She showed us how to ask AI for suggestions and then choose which suggestions to take. She also explained the difference between getting help and copying" (P08, Female, Year 2, International Trade).

Conversely, students who received no guidance reported more problematic use. A participant from Nigeria stated: "None of my teachers talk about AI. Maybe they don't know about it. I just do what I think is okay. Sometimes I think maybe I am doing something wrong, but nobody tells me. I just continue" (P11, Male, Year 2, Marine Engineering).

Some participants described innovative pedagogical approaches. A student from Uzbekistan reported: "My teacher actually encourages us to use AI, but she makes us explain our process. We have to show how we used AI, what we changed, why we changed it. She says this helps us learn to use AI as a tool, not as a replacement. I think this is very helpful because I learn from the process" (P06, Male, Year 1, Navigation).

5.4 Theme 4: Institutional and Cultural Contexts

Participants identified institutional and cultural factors that shaped their AI use. The vocational education context, with its emphasis on practical skills and industry preparation, created distinctive pressures and opportunities.

A third-year student from Myanmar reflected on the vocational context: "Unlike university students who study theory, we need practical skills. In navigation, I need to communicate with Chinese crew members. AI cannot help me in real situations. I must learn. This motivates me to use AI as a learning tool rather than just a tool for getting things done" (P14, Male, Year 3, Navigation).

However, the compressed timeline of vocational programs also increased AI dependency. A student from Indonesia observed: "We only have two years to learn Chinese. It's not enough time. So many of my classmates just use AI to pass the courses. They don't care about learning Chinese because they think they will use AI at work anyway. But I think maybe this is short-term thinking" (P03, Female, Year 1).

Cultural factors emerged as well. Participants from collectivist cultures described more reluctance to ask teachers for help, leading them to rely on AI as a non-face-threatening source of assistance. A student from South Asia explained: "In my culture, we don't want to bother the teacher. We try to solve problems alone. AI is a way to get help without asking anyone. This is good because we don't lose face, but maybe not so good because we don't learn from the teacher" (P10, Male, Year 2).

5.5 Theme 5: Articulated Support Needs and Recommendations

Participants identified several forms of support they desired regarding AI use in Chinese learning. These needs clustered into five categories:

First, explicit AI use guidelines. Participants consistently requested clear policies on what AI use is acceptable in different contexts (homework, exams, class participation, etc.). A student from Vietnam expressed this need: "I just want to know clearly: can I use AI for homework? Can I use it to prepare for class? What is okay and what is not okay? Then I will follow the rules" (P05, Female, Year 1).

Second, AI literacy training. Participants wanted instruction in effective and ethical AI use. A student from Thailand said: "I know AI is useful, but I don't know how to use it well. I want a class or workshop about how to use AI effectively, how to check if AI gives correct information, how to use AI to help my learning without becoming dependent" (P08, Female, Year 2).

Third, teacher modeling and integration. Participants wanted teachers to model appropriate AI use and integrate AI literacy into coursework. A participant from Pakistan explained: "If teachers show us how they use AI, and if they explain their thinking about AI use, this would help us learn. It should be part of the class, not something separate" (P07, Male, Year 2).

Fourth, peer learning opportunities. Participants desired structured opportunities to learn from more experienced peers. A student from Kenya noted: "My older friend who has been here longer knows how to use AI better. Maybe if the school organized a workshop where senior students share their strategies, this would help new students" (P09, Female, Year 2).

Fifth, balanced assessment approaches. Participants wanted assessment methods that acknowledge AI use while still testing genuine competence. A student from Uzbekistan articulated this: “If exams require us to use AI, but also test our understanding, this would be better than pretending AI doesn’t exist. The teachers should design tasks where AI use is part of the task, but you still need to understand what you are doing” (P06, Male, Year 1).

6. Discussion

6.1 Synthesis of Findings

This study provides empirical evidence on the patterns, effects, and moderating factors of AI tool usage in Chinese language learning among international students in Jiangsu vocational colleges. By integrating quantitative survey data with qualitative interview data, we have captured both the prevalence and the lived experience of AI-related phenomena. Several findings merit emphasis.

Widespread Adoption with Differential Effects. Nearly 90% of participants used AI tools for Chinese learning, confirming that AI integration is not a future possibility but an existing reality. However, the dual nature of AI effects—both empowerment and divide—was clearly evident. Frequent use was associated with both greater benefits (higher empowerment) and greater risks (higher divide effects). This finding challenges simplistic narratives of either technology salvation or technology threat.

The Critical Role of AI Literacy. AI literacy emerged as the strongest predictor of empowerment and a robust protective factor against divide effects in both quantitative and qualitative analyses. Participants with higher AI literacy reported greater benefits and fewer negative consequences from AI use. This suggests that the focus of institutional intervention should be on developing students’ capacity to use AI effectively and critically, rather than on simply prohibiting or permitting AI use.

Language Proficiency as a Gatekeeper. HSK level significantly moderated the relationship between AI usage frequency and divide effects. Lower proficiency students were substantially more vulnerable to the negative consequences of AI use. This finding has important implications for equity: the very students who may benefit most from AI support are also most at risk of AI-induced learning compromise. This represents a new form of digital divide—what we term the “AI competence divide” or “AI literacy divide”—that compounds existing linguistic disparities.

Teacher Guidance as a Protective Factor. Teacher guidance emerged as a significant predictor of both empowerment and divide effects, and qualitative findings confirmed that teacher practices varied dramatically. Students who received clear guidance reported more balanced, empowering usage. Students who received no guidance reported confusion, guilt, and problematic usage patterns. This suggests that teacher professional development regarding AI integration is a high-priority institutional intervention.

Vocational Context as a Shaping Force. The vocational education context—characterized by shorter program duration, practical skill emphasis, and industry preparation — shaped AI usage patterns. The compressed timeline increased AI dependency, while the practical emphasis motivated more strategic use among some students. This suggests that interventions need to be context-sensitive, accounting for vocational education’s distinctive features.

6.2 Theoretical Contributions

This study makes three theoretical contributions.

First, it extends van Dijk’s (2024) digital divide framework to the context of AI-enhanced language education. Our findings demonstrate that the “skills access” and “usage access” levels are particularly consequential in AI contexts. Students may have equal physical access to AI tools yet differ dramatically in their capacity to use them effectively and critically. The “AI literacy divide” represents a new, consequential form of digital inequality that has received insufficient attention in prior scholarship. We propose that van Dijk’s framework be extended to include “AI literacy access” as a distinct level, or at minimum, that skills access be operationalized to include AI-specific competencies.

Second, the study contributes to understanding the conditions under which technology enhances versus hinders learning. The “empowerment-divide dualism” we observed is consistent with the technology mediation literature, which suggests that the effects of technology are not inherent but are shaped by user characteristics, social context, and pedagogical design (Warschauer, 2011). Our moderation analyses identified AI literacy, teacher guidance, and language proficiency as critical shaping factors. This supports a socio-technical perspective in which outcomes are co-produced by technology, user, and context.

Third, the study provides empirical grounding for conceptualizing AI literacy in language learning contexts. While prior research has proposed AI literacy frameworks (Long & Magerko, 2020; Ng et al., 2021), few have empirically validated these frameworks in specific learning contexts. Our findings suggest that AI literacy for language learning includes both general AI competencies (understanding capabilities and limitations, critical evaluation) and language-learning-specific competencies (integrating AI use with language development goals, understanding the relationship between AI assistance and communicative competence).

6.3 Practical Implications

AI Literacy Integration. The primacy of AI literacy suggests that vocational institutions should integrate AI literacy training into their curricula. Such training should cover: understanding what AI can and cannot do for language learning; formulating effective prompts; critically evaluating AI output; using AI as a tool for learning rather than a replacement for learning; and maintaining academic integrity while using AI. This integration should occur both through dedicated workshops and through integration into existing language courses.

Differentiated Support Based on Proficiency. Given that lower proficiency students are most vulnerable to negative AI effects, institutions should provide targeted support to this group. This could include: closer monitoring of AI use in lower-level language courses; explicit instruction on appropriate AI use; and reduced reliance on homework formats that incentivize unreflective AI use.

Teacher Professional Development. The significant role of teacher guidance suggests that institutions should invest in teacher professional development regarding AI integration. Teachers need support in: understanding AI tools and their implications; developing AI-aware pedagogical strategies; communicating clear expectations to students; and designing assessments that appropriately account for AI use.

Clear Institutional Policies. Qualitative findings revealed widespread confusion among students about acceptable AI use. Institutions should develop clear, accessible policies that specify what AI use is appropriate in different contexts (homework, exams, class participation, preparation, etc.). These policies should be developed with student input and should be reviewed regularly as AI technology evolves.

Assessment Reform. The prevalence of AI use suggests that traditional assessment methods—particularly unsupervised homework and take-home assignments—may no longer validly assess student competence. Institutions should consider: in-class, supervised assessments; assessments that explicitly incorporate AI use; process-oriented assessments that evaluate students' engagement with AI; and oral assessments that test authentic communicative competence.

Peer Learning Programs. Given the value of peer learning, institutions might establish peer mentoring programs where more experienced students share AI strategies with new students. This would complement formal instruction with practical, peer-validated strategies.

6.4 Limitations and Future Directions

Cross-Sectional Design. The cross-sectional nature precludes causal inferences. Terms like "predict" are used in a statistical sense, not to imply causality. Future research should employ longitudinal designs to track how AI usage patterns and effects evolve over time, particularly as students' Chinese proficiency improves and as AI technology continues to develop.

Sampling Limitations. Data were collected from three institutions in Jiangsu Province, limiting generalizability to other regions and other types of institutions (research universities, non-vocational colleges). Future research should employ multi-site designs across different provinces and institution types. Jiangsu's economic development and technological infrastructure may differ from other regions, particularly inland provinces.

Self-Report Measures. Reliance on self-reported data may introduce common-method bias, social desirability bias, and memory limitations. Future research should incorporate behavioral data (actual AI usage patterns from device logs), observational data (classroom AI use), and performance data (learning outcomes) to triangulate self-report findings.

Limited General AI Literacy Measures. Our AI literacy measure, while based on prior frameworks, was developed for this study and has not been extensively validated. Future research should develop and validate comprehensive AI literacy instruments appropriate for language learning contexts.

Limited Attention to Tool-Specific Effects. This study examined AI tool usage broadly, without systematically distinguishing effects across tool categories. Different AI tools may have different empowerment-divide profiles. Future research should examine whether translation tools, conversational AI, writing assistants, and other categories have systematically different effects.

Cultural Group Comparisons. While our sample included participants from multiple regions, the sample sizes for subgroup comparisons were limited. Future research with larger samples should explore whether AI usage patterns and effects differ systematically across cultural groups.

6.5 Conclusion

This study examined AI tool usage in Chinese language learning among international students in three Jiangsu vocational colleges using a sequential explanatory mixed-methods design. Nearly 90% of participants used AI tools for Chinese learning, with translation tools being most common. AI use was associated with both empowerment effects (efficiency, personalized support, barrier reduction) and divide effects (technological dependency, critical thinking erosion, academic integrity concerns). The balance between empowerment and divide was significantly moderated by AI literacy, teacher guidance, and Chinese language proficiency. Qualitative findings revealed that participants experienced AI as a "necessary crutch" and articulated clear needs for explicit guidelines, literacy training, teacher modeling, peer learning, and balanced assessment.

The findings extend digital divide theorizing to AI-enhanced language learning contexts, highlighting the "AI literacy divide" as a new form of educational inequality. They also provide practical guidance for vocational institutions seeking to help international students use AI responsibly and effectively. As AI technology continues to advance and integrate into educational settings, developing students' AI literacy and creating supportive institutional environments will be essential for ensuring that AI empowers rather than divides.

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References

[1] Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

[2] Berry, J. W. (1997). Immigration, acculturation, and adaptation. Applied Psychology: An International Review, 46(1), 5–34. https://doi.org/10.1111/j.1464-0597.1997.tb01087.x

[3] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

[4] Brislin, R. W. (1970). Back-translation for cross-cultural research. Journal of Cross-Cultural Psychology, 1(3), 185–216. https://doi.org/10.1177/135910457000100301

[5] Chen, L., Chen, P., & Lin, Z. (2023). Artificial intelligence in education: A systematic review of adaptive learning systems. Computers & Education, 198, 104767. https://doi.org/10.1016/j.compedu.2023.104767

[6] Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.

[7] 2190148

[8] Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.

[9] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

[10] Field, A. (2018). Discovering statistics using IBM SPSS statistics (5th ed.). SAGE Publications.

[11] Gagné, M., & Deci, E. L. (2005). Self-determination theory and work motivation. Journal of Organizational Behavior, 26(4), 331–362. https://doi.org/10.1002/job.322

[12] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.

[13] Krashen, S. D. (1985). The input hypothesis: Issues and implications. Longman.

[14] Li, Y., Wang, X., & Zhang, Q. (2021). Self-assessment of Chinese proficiency among international students: A validation study. Journal of Chinese Language Teaching, 18(3), 45–68.

[15] Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–16. https://doi.org/10.1145/3313831.3376727

[16] Ministry of Education of the People's Republic of China. (2025). Statistical report on international students in China 2024. Ministry of Education.

[17] Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, 100018. https://doi.org/10.1016/j.caeai.2021.100018

[18] Norris, P. (2001). Digital divide: Civic engagement, information poverty, and the Internet worldwide. Cambridge University Press.

[19] Patton, M. Q. (2015). Qualitative research & evaluation methods (4th ed.). SAGE Publications.

[20] Rubin, H. J., & Rubin, I. S. (2012). Qualitative interviewing: The art of hearing data (3rd ed.). SAGE Publications.

[21] Swain, M. (1995). Three functions of output in second language learning. In G. Cook & B. Seidlhofer (Eds.), Principle and practice in applied linguistics (pp. 125–144). Oxford University Press.

[22] Van Dijk, J. A. G. M. (2005). The deepening divide: Inequality in the information society. SAGE Publications.

[23] Van Dijk, J. A. G. M. (2024). The digital divide (2nd ed.). Polity Press.

[24] Ward, C., & Kennedy, A. (1999). The measurement of sociocultural adaptation. International Journal of Intercultural Relations, 23(4), 659–677. https://doi.org/10.1016/S0147-1767(99)00014-0

[25] Warschauer, M. (2011). Learning in the cloud: How (and why) to transform schools with digital media. Teachers College Press.